What could we learn about climate sensitivity from variability in the surface temperature record?

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Introduction

We consider the question of what can be learned about the equilibrium climate sensitivity (S) from interannual variability in the observed temperature record. Our analysis is performed within the paradigm of a perfect model experiment, in which synthetic time series of annual temperature anomalies are generated from a simple climate model with known parameters and observed with no observational error or uncertainty, and we attempt to deduce the parameters from the variability in the time series.

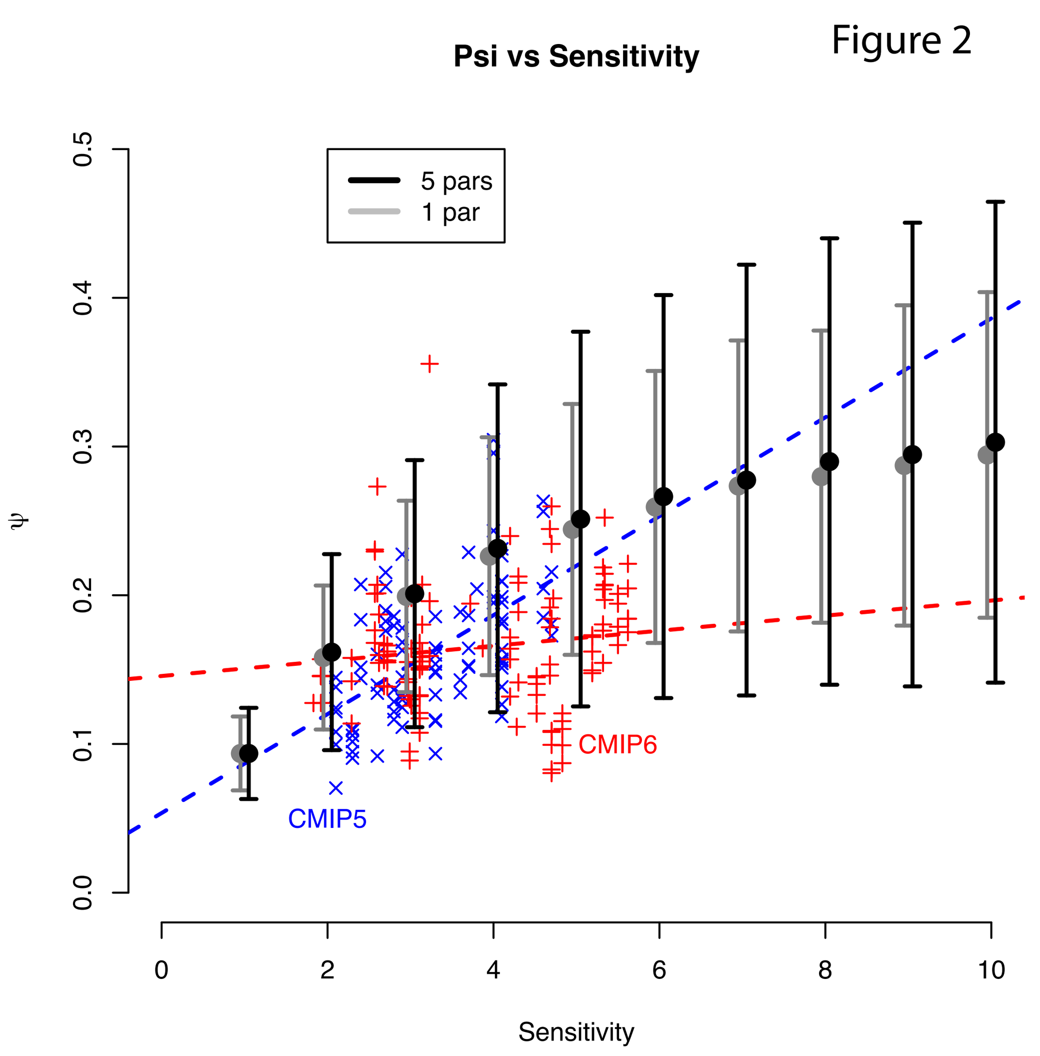
Results - 1. How does Psi vary with equilibrium climate sensitivity?

Psi is a scalar measure of variability, that Cox et al (2018) used as an emergent constraint on sensitivity. Figure 2 shows how Psi varies with sensitivity in this simple model, when other parameters are held fixed (grey dots/bars) or when 3 other model parameters (and aerosol forcing) also vary in reasonable ranges (black dots/bars). Each bar summarises the mean and 95% range of Psi calculated from an ensemble of simulations of the historical period, that vary in their sample of internal variability.

Psi generally increases with sensitivity, but as shown in the Figure there is substantial nonlinearity in the response and also large uncertainty in the value of Psi obtained from a single model run due to the random sample of internal variability noise.

Results from CMIP5 and CMIP6 ensembles are also shown together with the best straight line fit to these points. While both ensembles are broadly consistent with our simple model results and show a positive correlation, there is wide scatter about the best linear fits, which also differ substantially between generations.

Figure 2



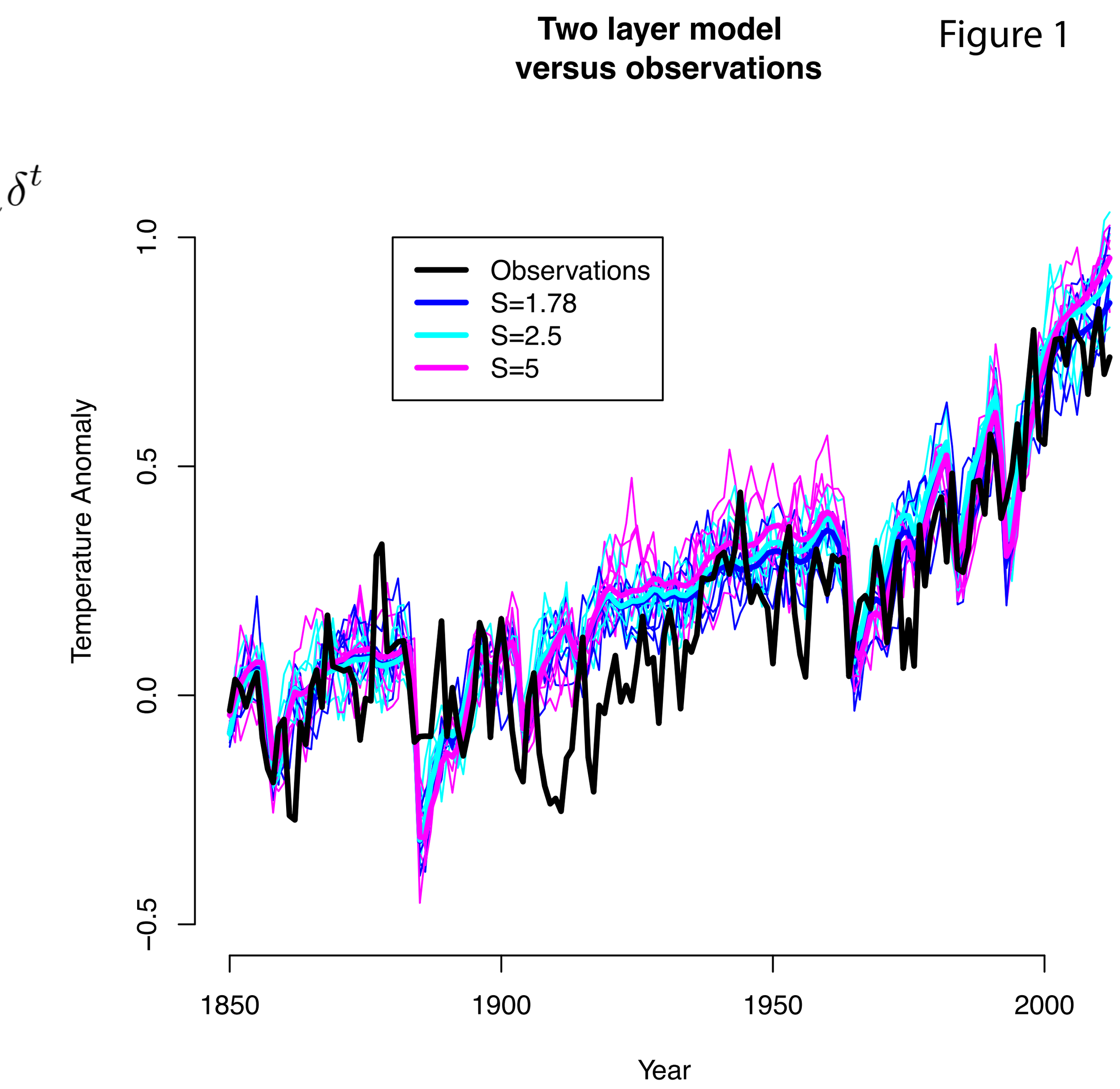
Model

$$C_m \frac{dT_m}{dt} = F^t + \lambda T_m - \epsilon\gamma(T_m - T_d) + C_m \delta^t$$

$$C_d \frac{dT_d}{dt} = \gamma(T_m - T_d)$$

The model is a standard 2-layer energy balance, with the Held/Winton (2010) heat uptake efficiency factor (but this does not affect our results) and Hasselmann (1974) white noise internal variability term. When forced appropriately, it can reproduce the 20th century global temperature time series reasonably well for a wide range of sensitivity values, as shown in Figure 1. Note that other model parameters also vary in these runs.

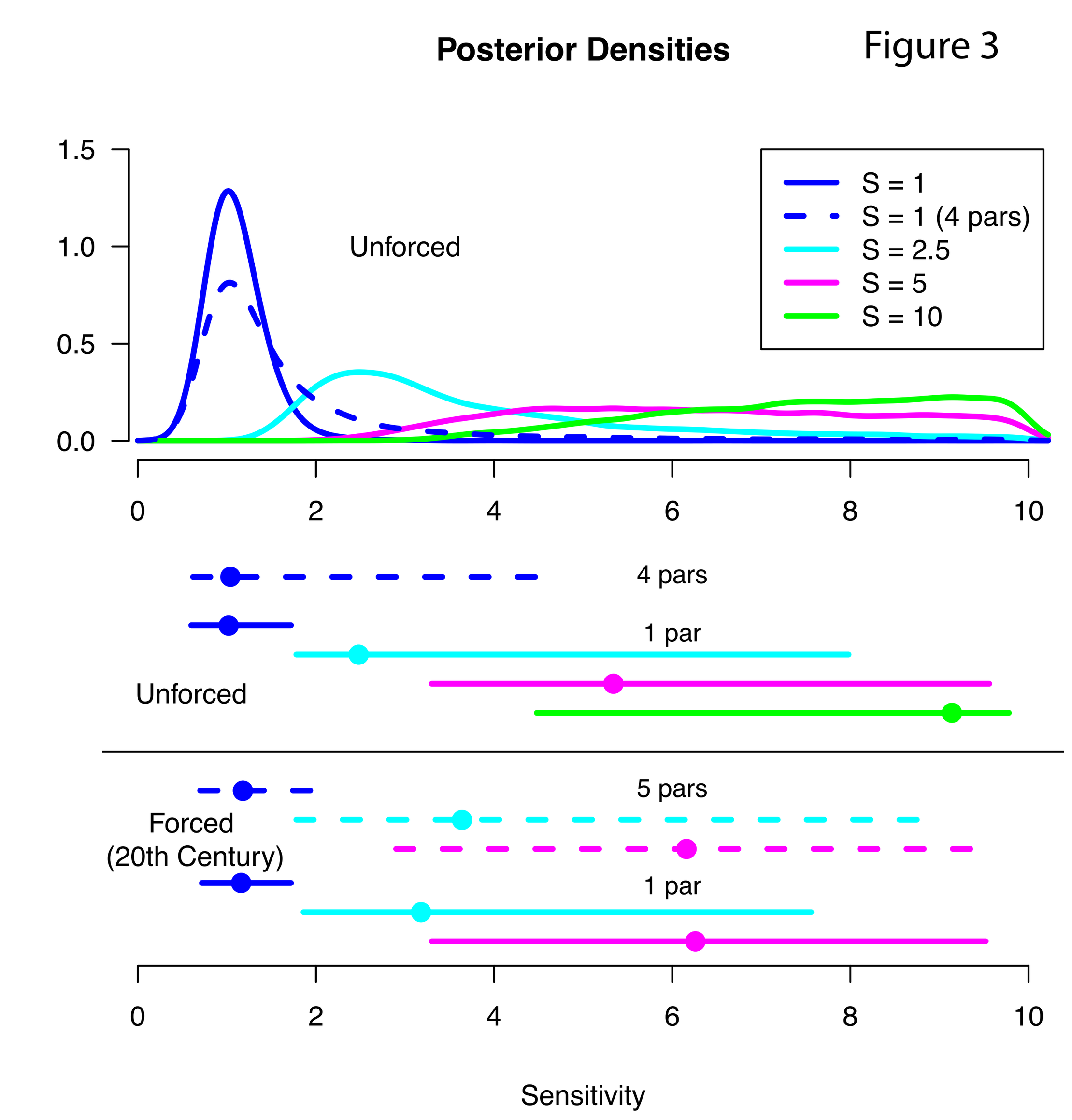
Figure 1



Results - 2. Bayesian estimation of sensitivity using an observation of Psi

We can perform a standard Bayesian estimation procedure based on an observation of Psi. In Figure 3, we show results both from 150y unforced simulations (ie, where the only source of variation is internal variability) and simulations of the historical period. Curves in top panel are posterior pdfs (equivalently, likelihoods, as we are using a uniform prior for S) for the unforced case. Lines below show mode and 5-95% ranges for these unforced experiments and also forced experiments with either 1 or 4 uncertain parameters (and aerosol forcing where present). We see that a tight constraint is obtained when the sensitivity is extremely low, but not otherwise.

Figure 3



More details:

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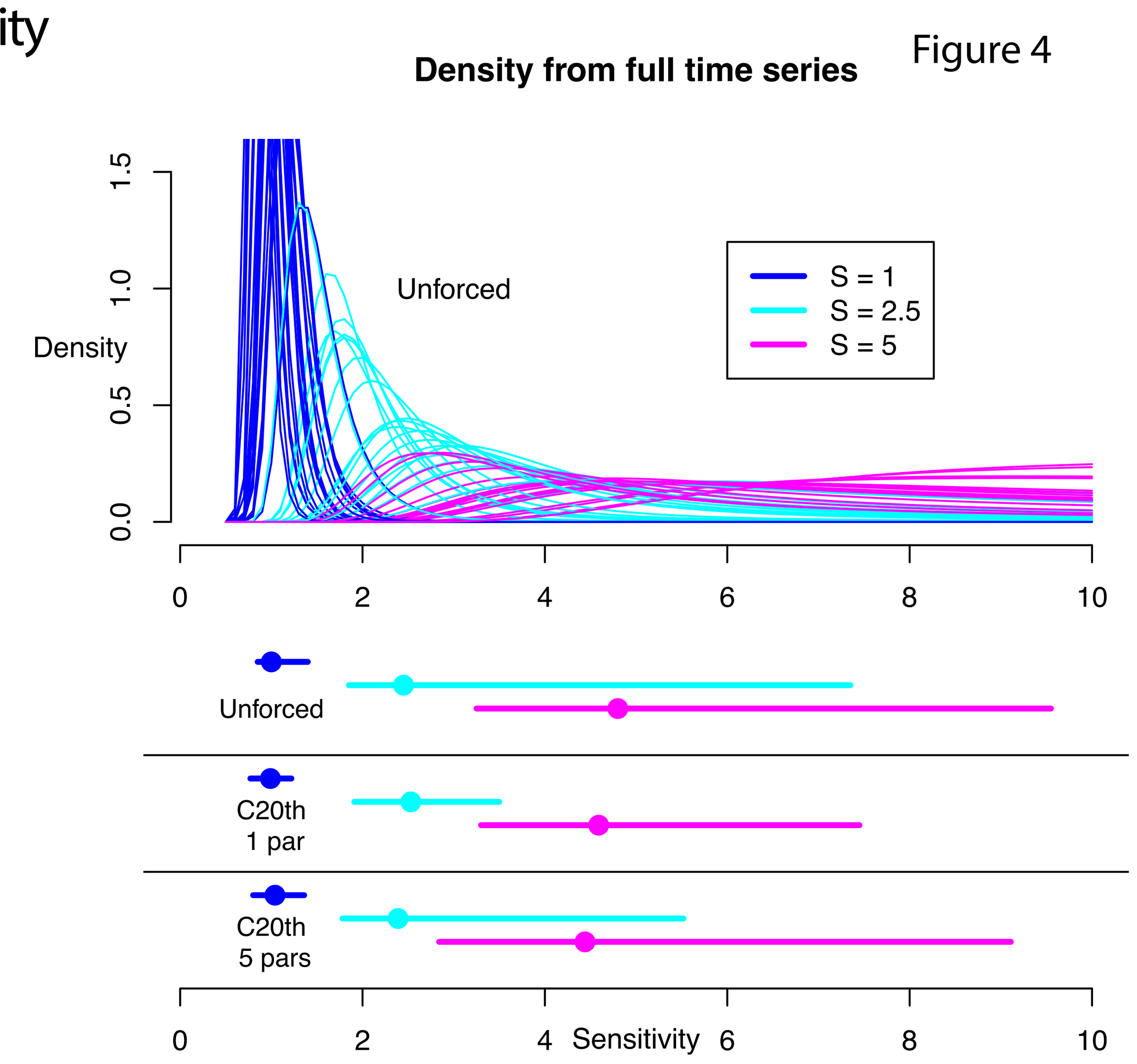
Results - 3. Using the full time series of variability

Psi is a statistical summary of the time series, and it could be hoped that more information may be contained in the full time series of annual temperature anomalies. With our experimental setup, it is possible to perform a precise calculation the exact likelihood of this specific time series of model results (up to the numerical precision of the computer). Figure 4 shows the posterior pdfs (likelihoods) for multiple samples of internal variability, for each of three different sensitivity values. The dots and bars show the medians of the maximum likelihood and of the 5-95% ranges from the 20 replicates, both in forced and unforced cases. It seems from comparison of this analysis to Figure 3 that the use of psi is not generally a limiting factor: in fact it represents most of the information of the time series in a generally adequate manner. However, there is not really that much information to summarise.

Figure 4



Conclusion

Variability is linked to sensitivity, but this link is fairly weak and imprecise, even in this "perfect model" scenario with a simple energy balance model and perfect observations. We do not believe that the variability of the 20th century can be used to obtain a strong constraint on the sensitivity, but we do think that methods that rely on a long-term warming trend or difference may be throwing away useful information.

References

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